Bachelor's thesis

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Faculty of Economics and Management
NTNU Business School

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Can the inclusion of green initiatives variables help us explain the electricity price more accurately?

Bachelor's thesis in Economic and Management
Supervisor: Denis M. Becker
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Preface

During our time at NTNU Business school, we have acquired the foundational knowledge necessary to complete this thesis. This paper represents the culmination of our bachelor's degrees in economics and management in Trondheim, with a focus on Business Analytics. We have drawn extensively from the insights gained in the courses "BBAN3001 – Essentials of Business Analytics" taught by Denis M. Becker and "MET2010 - Applied Statistics" instructed by Johannes Mauritzen. These courses have not only provided a solid basis for our thesis but also piqued our interest in the rapidly evolving field of business analytics and making good data-driven decision withing the fields of economics, finance, and management.

After a year where the power balance in Europe and the rest of the world is shifting. Where we are in the start of a green shift within the energy balance going from a more Co2 tilted energy mix to the use of more electricity based. The energy sector has undergone a transformation in recent years, as governments and businesses increasingly prioritize sustainable development. Green initiatives such as renewable energy generation, energy efficiency improvements, and carbon emissions reductions have gained traction as means of mitigating climate change and promoting sustainable growth. In this context, the electricity price has emerged as a key variable in understanding the economic impact of green initiatives.

The purpose of this paper is to investigate whether the inclusion of green initiatives variables can help us explain the electricity price more accurately. Specifically, we will analyze the relationship between green initiatives and electricity prices by testing the hypothesis that green initiatives have a statistically significant impact on electricity prices.

Working on this thesis has not only given us new insights on our understanding of data science and energy economics, but also provided valuable experience in collaborating within a large team. The group dynamics have facilitated the exchange of diverse perspectives, improvement of individual work quality, and skills development among team members.

We would also like to express our profound gratitude to Dennis M. Becker for his valuable academic guidance and steadfast support throughout our bachelor thesis.

Adrian Gyberg | August Hereid Ringheim | Frederik Lager Selvik

Markus Rusti | Rasmus Oliver Hilstad Hopen | Viljar Ødelien

Trondheim, April 20th, 2023

Abstract

The rapid expansion of renewable energy sources and green initiatives has transformed the power market landscape. This bachelor thesis examines the role of green initiatives in explaining electricity price fluctuations more accurately by employing Ordinary Least Squares (OLS) regression models. Two models are compared in this thesis: one incorporating green initiatives variables, and another excluding them.

The green initiatives variables consist of initiatives from both the production and the consumption side of the energy balance. On the production side we are including variables from production of green electricity from windmills and on the consumption side we are including electrification of the Norwegian car fleet and the electrification of the Norwegian continental shelf. Lastly, we are also including the price of EU`s ETS CO2 allowances which is an initiative. These factors are integrated into the first model, while the second model solely relies on traditional factors. The analysis is conducted using historical data reaching from 2011 to 2022 and the specific area is NO1 or the south-east part of Norway.

Insights gained from our findings have facilitated a more profound comprehension of the factors influencing electricity prices, which is crucial for making accurate models for both explaining and predicting. It can be problematic to conclude that the inclusion of green initiatives will lead to a better OLS model. Because the manual selection of variables and interpolating of the data, in retrospect, could have potentially compromised the reliability of our findings. Furthermore, it is also important to mention that over-fitting of the model to the data can lead to problems when we are looking closer into other dataset with a different mix.

Sammendrag

Med økt bruk av fornybare energikilder og grønne initiativer vil det de kommende årene være en stor ending i strømmarkedet. Denne bacheloroppgaven undersøker rollen grønne initiativer kan ha å forklare endinger i elektrisitetspriser mer nøyaktig ved å benytte «Ordinary Least Squares» (OLS) regresjonsmodeller. Vi vil utarbeide to modeller som så skal sammenlignes i denne oppgaven: en som bruker flere variabler som man vet påvirker strømprisen videre en modell hvor variabler for grønne initiativer inkluderes.

Variablene som blir introdusert som grønne initiativer er både fra tilbuds og etterspørselssiden i energibalansen. På tilbudssiden inkluderer vi variabler fra produksjon av strøm fra vindmøller og på etterspørselssiden inkluderer vi elektrifisering av den norske bilparken og elektrifisering av den norske kontinentalsokkelen som står for produksjon av olje og gas. Til slutt inkluderer vi også prisen på EUs ETS CO_2-kvoter, som fungerer som et grønt initiativ. Analysen utføres ved hjelp av historiske data som strekker seg fra 2011 til 2022. Hvor det spesifikke området er vi tar for oss er NO1, eller sørøstlige delen av Norge som i oppgaven er betegnet som «OSLO».

Det vi har funnet har gitt oss en bedre forståelse av de ulike faktorene som påvirker strømprisen, noe som er avgjørende for å lage nøyaktige modeller både for prediksjon og forklaring. Det kan være problematisk å konkludere med at det å inkludere grønne initiativer vil føre til en bedre OLS-modell. Grunnen for dette er at valgene vi har valgt rundt variabler samt interpolering av dataene kan ha svekket påliteligheten til resultatet videre er det sentralt å trekke inn at overtilpassing av modellen til dataen også kan være et problem.

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1. Introduction

Most of the electricity production in Norway is based on renewables, making Norway one of the frontiers in green electricity production. About 92% of the electricity production in Norway is based on hydropower and some smaller shares of wind with 6.5%. (IEA, 2022)

However, an increasing demand for electricity is coming because of the green shift, whereas Norway's power production must increase by a whole 50% as of 2030. In the following years, the Norwegian electricity demand will increase dramatically following the electrification of the continental shelf, industry, and transportation (PwC, 2022). Especially considering the increased demand for electricity when taking the electrification of the continental shelf into account, which alone is predicted to stand for 5% of the total demand for electricity in Norway by 2025 (NVE, 2020, p. 9).

One of the potential results of not producing enough electricity, could therefore be an increased price contagion from Europe, which could give serious consequences for both businesses and private households alike (PwC, 2022). The Norwegian consumer council has already expressed concerns regarding the economic implication for low-income households (Forbrukerrådet, 2022).

To examine the impact of including data on green initiatives on the accuracy of our model, we will analyze historical data on electricity prices and green initiatives and develop an explanatory model that considers the impact of green initiatives on electricity prices. To approach this task, we will proceed by constructing a base model that does not take any considerations for green initiatives. Subsequently, we will incorporate the green initiatives with the aim of increasing the effectiveness of the model. To summarize, this brings us to the thesis problem:

Can the inclusion of green-initiatives variables help to explain the electricity price more accurately?

The thesis is structured as follows: In Chapter 2, we will provide a review of existing research concerning using linear regression models for electricity price modeling. Furthermore, we will present an overview over the Norwegian electricity market, the power mix, and discuss our chosen green initiatives to present their relevance. In Chapter 3, we will describe the methodology used in our study, including our data and independent- and dependent-variables. In Chapter 4, we will present both OLS models and check both their explanatory and predictive capabilities. Finally, in Chapter 5, we will summarize our findings, provide recommendations for future research, and draw conclusions.

2. Theory

Existing literature

From the literature, we mainly find electricity prediction models rather than explanatory models, whereas ARIMA and artificial neural networks (ANN) are popular models for such tasks (Monteiro et al., 2015). However, for this thesis, we wish only to look at relationships for a potentially better understanding of the nature of the new emerging green policies effect on the electricity market. Also, electricity price research, the literature seems to favor prediction rather than explanation – however these two are closely related considering one is often necessary for the other.

According to an article regarding linear regression (Ferreia et al., 2019). Linear regression pattern can be a useful tool for forecasting electricity prices, where the authors chose to focus on the Iberian electricity market. The study proposes a linear regression pattern for forecasting electricity prices in the Iberian electricity market. The model incorporates variables such as electricity demand, wind energy production, and temperature to predict hourly electricity prices. The results of the study suggest that the model performs well in predicting both normal and extreme price events. Specifically, the model can capture the effects of different input variables on the predicted electricity prices and outperforms some other commonly used forecasting methods. Therefore, the findings suggest that the proposed linear regression pattern can be a useful tool for forecasting electricity prices in the Iberian electricity market.

Dudek (2016) examined the use of linear regression (LR) and multilayer perceptron, a type of artificial neural network (ANN) for electricity price forecasting. Initially, two LR models were built, but they did not provide satisfactory results, so additional input variables were introduced to LR to model the nonlinear relationship between the input and output variables. Essentially, this brings us to the fact that multiple linear regression assumes that the relationship between the predictor variables and the response variable is linear, which may not always be the case.

A typical problem in all statistical modeling is over- and underfitting of the model to the data that it is given. (Khalaf & Zaman, 2015) The problems occur when the model we are choosing to use is either too complex or too simple for the data, leading to poor performance when trying to make predictions. Overfitting occurs when the model is too complex and captures the noise in the data, resulting in high accuracy on the training set but poor generalization on new data. On the other hand, underfitting occurs when the model is too simple and cannot capture the underlying patterns in the data, resulting in poor performance on both the training and test sets. To test how the performance and compare the model the dataset is split up in a test and a training set to compare how the model are working on both sets R^2. (Khalaf & Zaman, 2015)

The study by Ferreia et al. (2014) highlights the usefulness of linear regression for predicting electricity prices in the Iberian electricity market. However, the study by Dudek (2016) reminds us that we should be aware of the limitations of linear regression and that it may not always capture the non-linear relationship between predictor variables and the response variable. Therefore, while linear regression may be a good method for explaining correlations in some cases, it is important to keep in mind the potential for non-linearity and consider other modeling techniques if necessary.

The Norwegian electricity market and energy mix

The electricity market is complicated due to the unique nature of electricity production and consumption. Electricity must be used as soon as it is produced, leading to a market which is homogenous and challenging to distinguish between the different producers and consumers in the given markets. Further on the connection between the markets and how the markets are intertwined in each other leads to a big and complex market system with several components. Our thesis will mainly focus on the northern European market where the market maker is Nord Pool owned by Euronext and the transmission system operators (TSO) in the Nordic countries; Statnett, Svenska Kraftnät, Fingrid Oyj, Energinet, Litgrid. The producers of energy in different countries (Ministry of Petroleum and Energy, 2015). Our thesis focuses on the Norwegian power market with the market zones NO1-NO5.

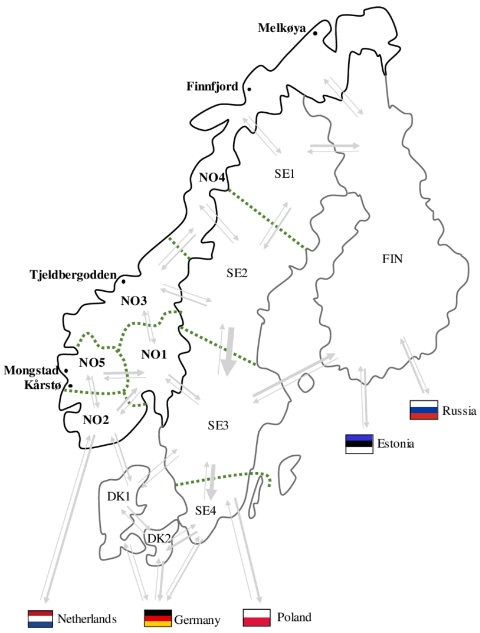


Figure 1: Overview of the different price zones (Clauß et al., 2018)

Structure of the power market

The energy market in Norway operates in a competitive market structure, where various actors participate in the production and sale of energy. The market is structured by the principles of supply and demand and is designed to ensure that the price of electricity reflects the cost of production and distribution. This market structure is a tool to gain optimal production given the demand. The main platform for determining the spot price for electricity in Norway is the Nord Pool Spot market, which is a single market for the Nordic countries and the market is entangled with the rest of the European Union, which is regulated by ACER on behalf of the EU third energy package.

According to a report by the International Energy Agency (IEA, 2022), the Nord Pool Spot market operates through three main markets: the Day-ahead market, the Intraday market, and the Balance market. The Day-ahead market is a forward market where participants can place bids for the delivery of electricity the next day. The Intraday market is a real-time market that allows participants to buy or sell electricity on the same day of delivery. The Balance market is a market for the adjustment of imbalances between actual electricity consumption and the predictions made in the Day-ahead and Intraday markets. To always have a secure electricity delivery to the customer the balance market is divided into three reserve markets. These reserves will lead to a guarantee of electricity if the deviation from the day-ahead market is too big. (Norwegian ministry of petroleum and energy, 2022)

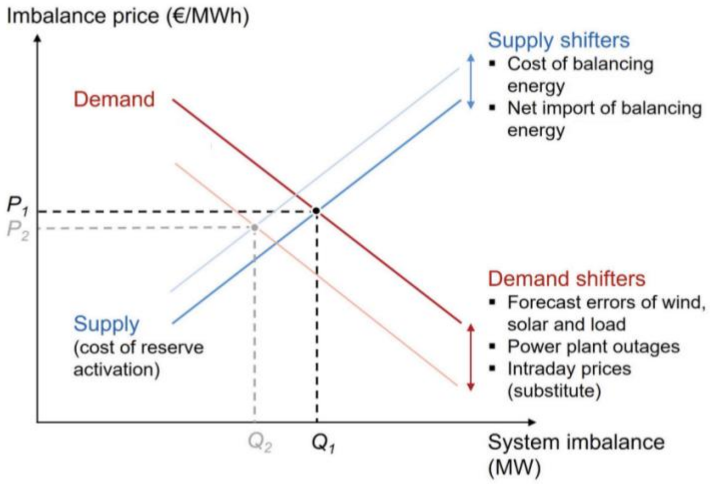


Figure 2: Regarding the equilibrium in the power market (Eicke et al., 2021)

Using this specific market structure, the electricity market operators get close to the goal of economic equilibrium as possible. Where the production/supply meets the given demand. Since energy must be used as soon as it is produced it is not a resource that can be stored.

By having a shift in demand, based on errors and deviations occurring in the power grid such as higher demand then planned from consumers or an error in production. This leads to a shift in the equilibrium, if the demand is higher there is a change, and it will lead to the usage of the capacity in the power reserves or import. If the production that is planned is higher than the actual consumption, there will be a price reduction. As listed in Figure 2 over, in electricity markets in general curves are changing at a high frequency, always going closer to the optimal equilibrium. (Eicke et al., 2021)

Energy Mix in Norway

The energy mix refers to the combination of different sources of energy that a country or region uses to meet its energy needs. This includes not only sources used for electricity production, but also sources used for heating, transportation, and other industrial purposes. The energy mix is an important factor that affects a country's energy security, economic development, and environmental sustainability. Changing the energy mix to reduce the carbon emission from the energy mix is the main reason why we have the green initiatives. (Miljødirektoratet, 2020) These changes lead to a higher electricity demand, meaning the production of energy resources each year needs to increase. (NVE, 2020)

In Norway, the energy mix is characterized by a strong reliance on hydropower for electricity production. According to data from the International Energy Agency (IEA, 2022), hydropower accounted for over 95% of Norway's electricity production in 2019. In addition to hydropower, Norway also has significant potential for the development of wind power, which is increasingly being utilized to complement hydropower in the production of electricity. The government of Norway has implemented various policies to promote the use of renewable energy sources and reduce the country's dependence on fossil fuels (NVE, 2020).

The green initiatives

Electrification of the Continental Shelf

The electrification of oil fields in Norway is a significant development in the country's energy sector. The process of electrification involves the use of electricity to power oil production instead of traditional gas turbines that are used. The change will reduce emissions and increase energy efficiency. This is in line with the country's goal to reduce its carbon footprint and transition to a more sustainable energy mix. Today the gas used to power the Norwegian oil rigs accounts for among 30 % of the country’s emissions (Meld.St. 36 (2020-2021)).

One of the key drivers of electrification in Norway is the demand for clean and efficient energy production in the oil and gas sector. The Norwegian government has set ambitious targets for emissions reductions in the sector, and electrification is seen as a key tool in achieving these goals (Equinor, 2021). The measures taken by the government to reduce the burden of the carbon footprint is to electrify the continental shelf with energy from the mainland. However, how electrification will affect the energy prices is currently unknown. It could potentially impact the pricing of the geographical zone it will be constructed in, or the whole Norwegian market. According to a report from the Norwegian Oil department ("Power from shore to the Norwegian shelf", chapter 6.3) the gathered power needed will be around 5,1 TWH. This will increase the demand for energy produced from the mainland which was 134 TWH in 2022 (IEA, 2022).

Wind power

Whereas the electrification of the Norwegian continental shelf may increase the demand for electricity, one of the newer green initiatives has been the recent development of wind power in Norway, which aims to increase the supply rather than demand. Wind power has been identified as a key area for growth in Norway's energy mix. The country has a long coastline and high wind speeds in many areas, making it well suited for wind power development (Rødland & Vevatne, 2020). The Norwegian government has set a target to have 10 TWh of wind power installed by 2030, which is expected to provide 10-15% of the country's electricity (NVE, 2021). Equinor has been testing offshore wind power in Scotland for the last 5 years, and the results seem to be positive. Since wind farms interfere with the local, untouched nature we urge to preserve near the coastline, offshore wind could be a good alternative. If this becomes a major part of the Norwegian energy market, it could impact the pricing of electricity severely.

Electric car subsidies

Another green initiative implemented by the government was subsidizing electric cars. Before January 2023, you could buy an electric car without paying VAT. From the beginning of 2023, VAT must be paid for the amount exceeding 500 000 NOK. In addition, electric cars were for a long period exempted from paying tolls and had free parking on public parking spots. The government provided incentives for the citizens to switch from fossil fuels into electric vehicles. Many of these incentives have been restricted as the population of electric vehicles has grown significantly. About 16 % of all cars in Norway are fully electric (SSB, 2022), and there is a growing trend. The consumption of energy only constitutes for about 0,6 % of the total energy production as of 2020 (Valle, 2021). The increase of electric vehicles could affect the energy prices for the consumer, it may not account for a large amount of the total consumption, but the capacity of the power grid is limited, which could lead to a demand higher than the grid can deliver in the future, especially combined with the electrification of everything else.

3. Method

Multiple Linear Regression

Multiple linear regression (MLR) is a statistical technique used for modeling and predicting the relationship between a dependent variable and one or more independent, explanatory variables (Spiegelhalter, 2020, p. 111). Multiple linear regression can be used to create an explanatory model for Norwegian electricity prices by identifying the relevant variables that may affect prices and analyzing their impact on the dependent variable (electricity prices) using regression analysis.

The resulting model can then be used to both predict future electricity prices and understand the factors that drive price changes in the Norwegian electricity market. The predictor variables can include various factors that are thought to have an impact on electricity prices, our dependent variable. MLR works by fitting a linear equation to the historical data that includes both the dependent and independent variables. The equation can be represented as

$$y = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \dots + \beta_n * x_n$$

Where y represents the dependent variable (electricity price), x_1, x_2, …, x_n represents the independent variables (predictor variables), β_0 represents the intercept, and β_1, β_2, …, β_n represents the coefficients that are estimated from the data. The coefficients represent the relationship between the dependent variable and each independent variable. Once the coefficients are estimated, the MLR model can be used to make assumptions about the electricity prices based on the values of the independent variables. The predictions are made by plugging in the estimated coefficients and the values of the independent variables into the linear equation. In the field of electricity price forecasting, MLR is often used because it is a simple and flexible technique that can handle multiple independent variables.

Measures of Model Performance

One of the most used criteria for evaluating models is the R-squared criterion. R-squared aims to explain the variance in our dependent variable by the variance in the independent variables. The value is often between 0 and 1, and the higher the number, the better the fit. Mathematically, it can be summarized as (Fabozzi et al., 2014, page 47-48):

$$\mathrm{R}^2 = 1 - \frac{\mathrm{RSS}}{\mathrm{TSS}}$$

Where RSS is the sum of squared residuals and TSS is the total sum of squares. However, it is important to note that R-squared always favors the most complicated model and increases the risk of overfitting. Taking this into consideration, we might also want to look at other criteria for comparison of the models. Two commonly known criteria are the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) (Fabozzi et al., 2014, page 399-403):

$$\mathrm{AIC} = -2 * \log(\mathrm{L}) + 2 * \mathrm{k}$$
$$\mathrm{BIC} = -2 * \log(\mathrm{L}) + \mathrm{k} * \log(\mathrm{n})$$

Where L is the likelihood of the model, k is the number of parameters and n is the sample size. Both evaluation criteria have the same aim - to identify the goodness of the fit for models. However, it is important to discuss how they function, and how they assess the evaluation in a different manner. The AIC and BIC are both based on the maximum likelihood estimation (MLE) method and aim to balance the number of parameters in the model with goodness of fit.

The main difference between AIC and BIC is the penalty term applied to the likelihood function. The AIC applies a penalty that increases with the number of parameters in the model, while the BIC applies a penalty that increases more strongly with the number of parameters. As a result, the AIC tends to favor more complex models than the BIC. This means that when comparing two models with similar fit, the model with more parameters will have a lower AIC, but may have a higher BIC (Fabozzi et al., 2014, 399-403).

4. Data

In this thesis, we examine the impact of including data on green initiatives on the accuracy of models explaining and potentially predicting the NO1 Spot price. Our data source is primarily publicly available data on wind power, electrification of the Norwegian continental shelf, and electric car adoption in Norway. However, we faced some challenges in obtaining data for electrification of the Norwegian continental shelf and electric cars in Norway, as there was not much information available. To overcome this challenge, we made some assumptions and calculated averages to have more usable data. However, it should be noted that making assumptions on missing data can lead to inaccuracies and potentially misleading results. In contrast, there was a lot more data available on wind power, and we were able to use this data with more confidence.

Dependent variable

Daily average electricity spot prices

The dependent variable in our thesis is the daily average spot electricity price across five power grid zones in Norway (NO1 to NO5) from 2011 to 2021. The electricity prices in the different zones serves as the dependent variable and is critical in our effort to predict future electricity prices. Our analysis of spot prices across all five zones allows us to assess the impact of independent variables, such as green initiatives, across different regions in Norway. The data was obtained from the Nordpool database, a trusted source for Nordic electricity market data. Figure 3 shows the prices for Oslo (NO1). The prices in the other zones would look similar, they correlate highly.

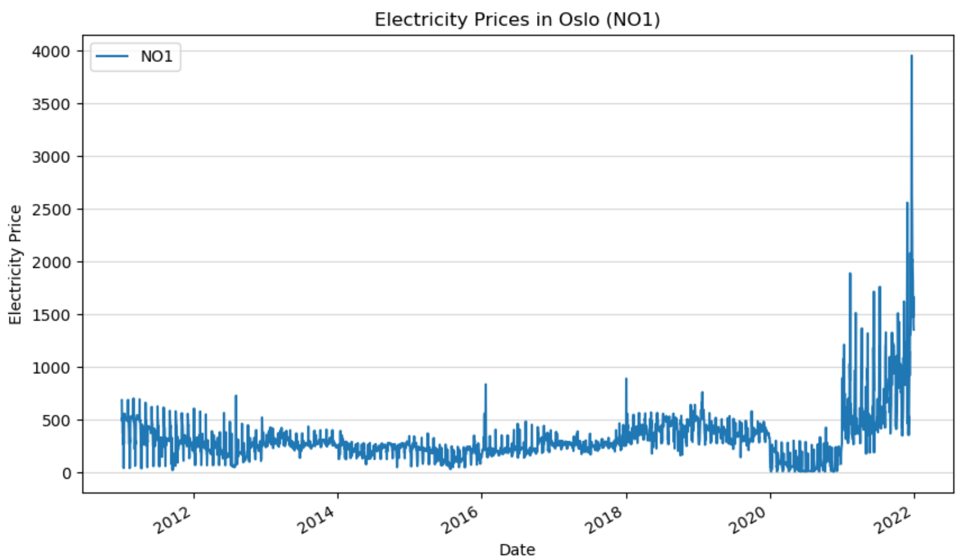


Figure 3: Electricity prices NO1 2011-2022 plotted using our dataset.

Independent variables for base model

The electricity price in Norway is a complex phenomenon that is influenced by numerous factors. The base model for predicting electricity prices in Norway aims to provide a benchmark by including the following key independent variables: Electricity prices in the surrounding power grid zones (Denmark DK1-DK2 and Sweden SE1-SE4), Degree of filling in water reservoirs, The power balance (Import and export), Temperature, and the Euro to NOK relationship. The purpose of the base model is to provide a reference point for comparison with the other model which includes data on green initiatives.

Electricity prices in the surrounding power grid zones

The independent variable Electricity Prices in the Surrounding Power Grid Zones examine the daily electricity prices in Denmark and Sweden from 2011-2021. These neighboring countries are included in the analysis as they are connected to the Norwegian power grid. This data is also sourced from Nordpool. The power grid zones in Sweden are designated as SE1-SE4 and in Denmark, they are designated as DK1-DK2. Understanding electricity prices in these interconnected regions provides valuable insights into the wider energy market and how it is connected to Norway. Figure 4 shows the electricity prices for the two main zones Stockholm and Copenhagen. We see that the zones almost always overlap, the other zones are highly correlated and will look similar.

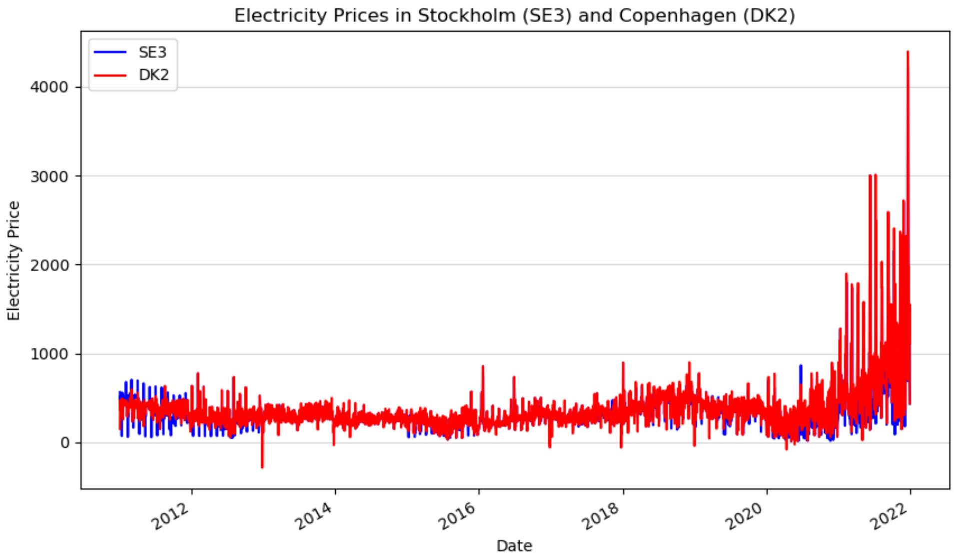


Figure 4: Electricity prices in Denmark and Sweden 2011-2022

Degree of filling in water reservoirs

The degree of filling in water reservoirs can have a significant impact on electricity prices. This information is collected weekly by Norges vassdrags- og energidirektorat (NVE) and ranges from 0 to 1. The level of water in the reservoirs directly affects the production of hydropower, which is a significant source of electricity in Norway. When there is a high level of water in the reservoirs, there is more available for power generation, leading to lower electricity prices (NTE, 2022). On the other hand, low levels of water can result in lower power production and increased prices. Figure 5 shows the Oslo fill degree, the fill degree for the other zones is highly correlated and would look similar. From figure 5, we observe that the fill degree is highly volatile, with seasonal changes being visible as repeating cycles of high to low values.

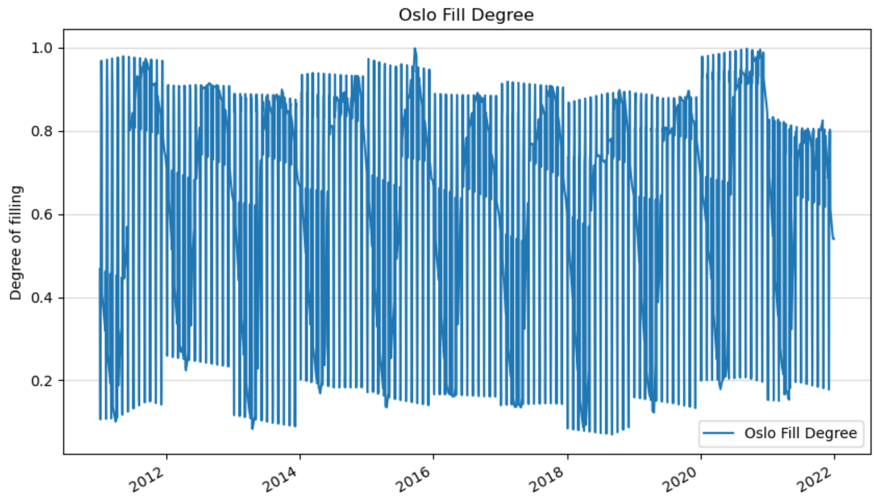


Figure 5: Degree of filling in Oslo water reservoirs 2011-2022.

Coal prices

The coal prices data is daily data fetched from Coal (API2) CIF ARA (ARGUS-McCl (MTF=F) (Yahoo Finance, 2023) and reflects the price of coal in the northwest region of Europe. This variable is relevant for predicting electricity prices as it is an important alternative to electricity in certain industries, especially in the production of heat and power. Changes in coal prices can have a direct impact on the cost of electricity production and ultimately affect the prices that consumers pay for electricity (NTE, 2022). Therefore, monitoring the trend of coal prices is important for predicting electricity prices, as it provides insight into the cost of one of the primary inputs used for electricity production. Figure 6 shows the movements in the coal price from 2011 to 2022.

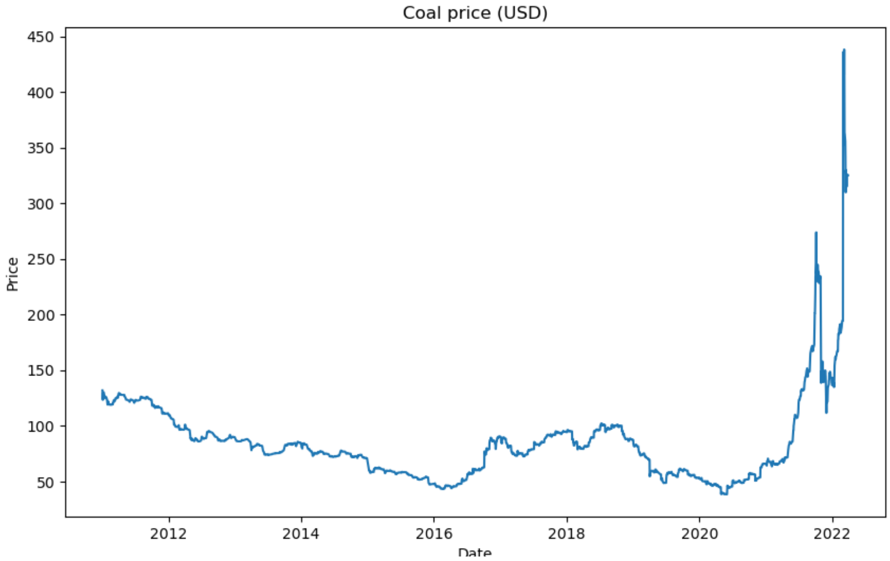


Figure 6: Coal price 2011-2022 plotted from our dataset.

Gas prices

In our study, the price data for the Natural Gas Mar 23 (NG=F) futures contract was obtained from Yahoo Finance. (Yahoo! Finance, 2023) This contract provides a means of tracking the price of natural gas, an alternative energy source that is becoming increasingly important. We have included this data in our base model for predicting electricity prices, as natural gas is often used as a fuel source for generating electricity. The daily data is showed in figure 7 and spans from 2011 to 2022, providing a comprehensive overview of the natural gas market over this period. This information is crucial in our analysis, as it allows us to consider the role of natural gas in the energy market and its potential impact on electricity prices.

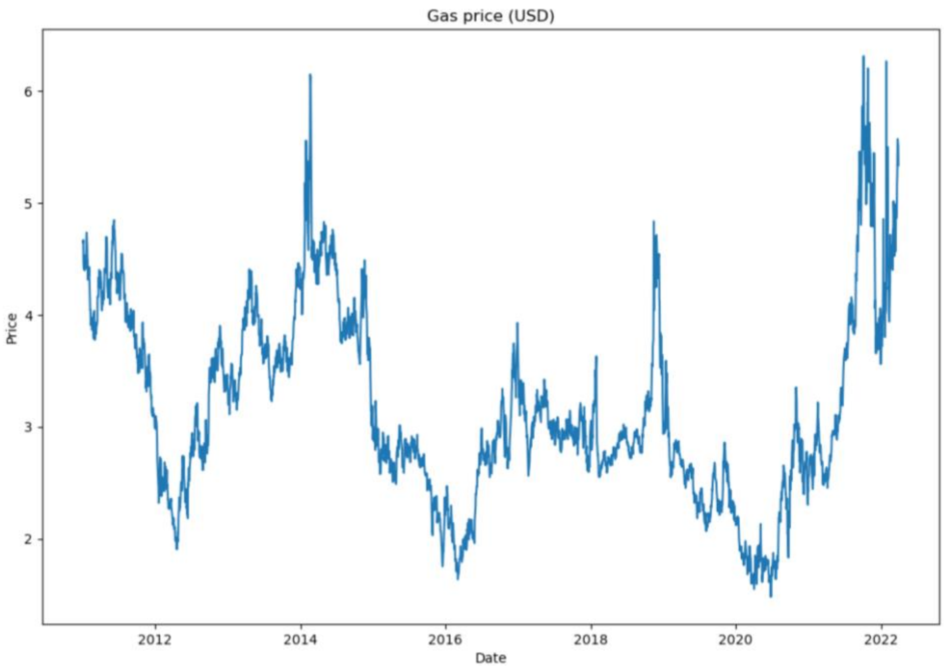


Figure 7: Gas prices 2011-2022 plotted using our dataset.

Power balance (Import and export)

As part of a global electricity market, Norway's electricity capacity for import and export is continually evolving, with power flowing across national borders. As such, electricity prices in Norway are directly and indirectly affected by prices on the continent and around the world (NTE, 2022). For this reason, we have retrieved the data from SSB - which consists of the monthly total import and export for Norway nationwide. Figure 8 shows import and export by quarters 2011-2022.

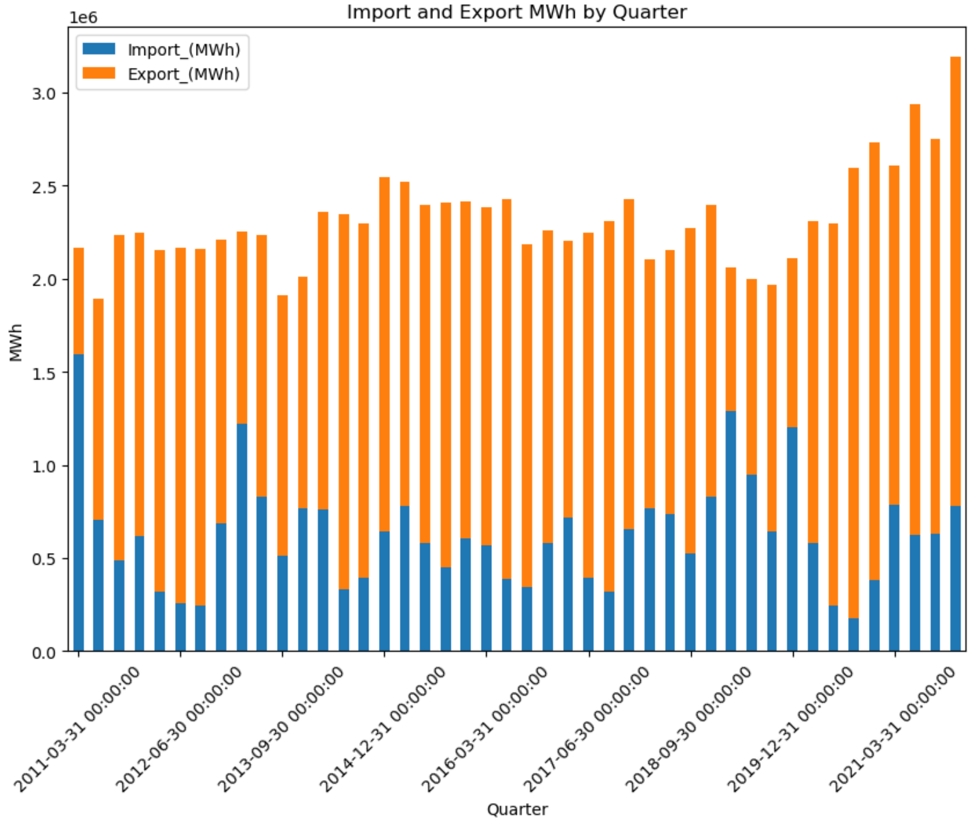


Figure 8: Norwegian import and export of power by quarter 2011-2022.

Temperature

Temperature is also an important variable for our base model, considering the demand for electricity goes up when the temperature goes down. When the demand goes up, the price also goes up (NTE, 2022). The data is from the Norwegian climate service center and represents the different regions we have as cities. (Norwegian center for climate services, 2022) The temperature data is used as an indication for seasons and can be used to differentiate seasonal changes in the different regions. Figure 9 shows the daily temperature in Oslo 2011-2022.

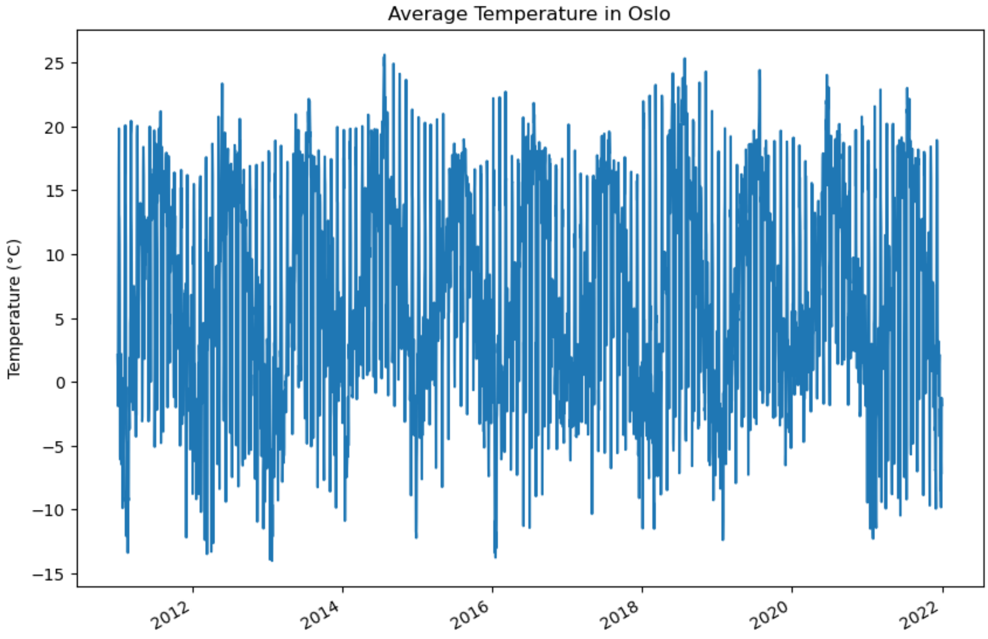


Figure 9: Temperature in Oslo 2011-2022 plotted using our dataset.

Euro to NOK relationship

NOK/EUR (NOKEUR=X) exchange rate data from Yahoo Finance shows the historical performance of the Norwegian Krone (NOK) against the Euro (EUR) from 2011-2022 shown in figure 10 (Yahoo Finance, 2023). The exchange rate affects the cost of imported goods and services, including energy sources, and therefore influences electricity prices in Norway. While the exchange rate is just one of many factors determining electricity prices, changes in the NOK/EUR exchange rate can impact the cost of imported energy and drive up or lower electricity prices (NTE, 2022).

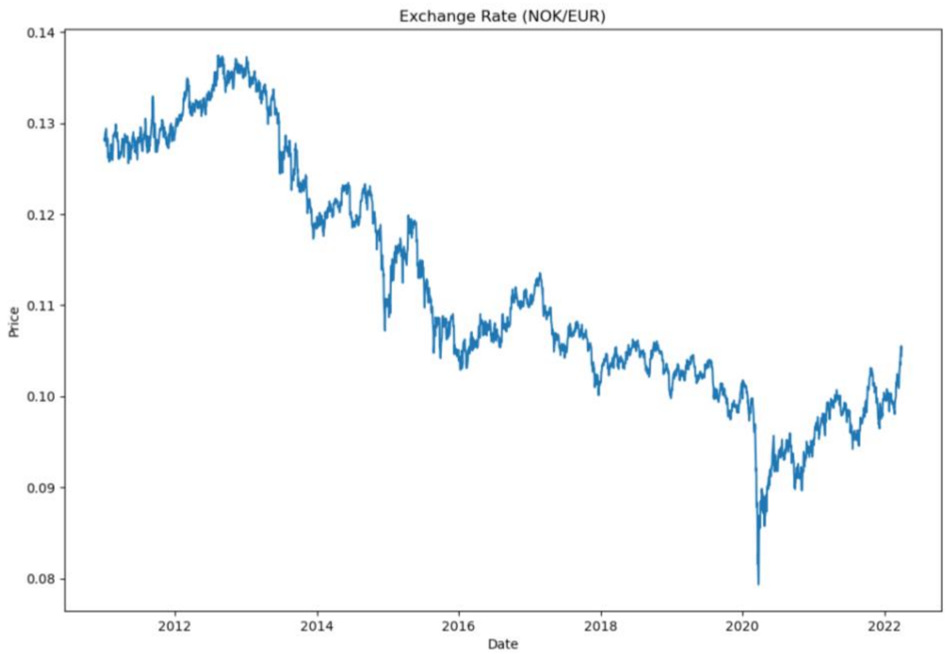


Figure 10: Euro/NOK exchange rate 2011-2022 plotted using our dataset.

Independent variables for green initiatives

Wind power production

We have retrieved daily data on wind power production in Megawatt-hours (MWh) from the period 2011-2021 shown in figure 11. The data is obtained from the "Norges vassdrags- og energidirektoratet" (NVE), and captures the daily production of wind power, which is an important aspect of the green energy initiatives.

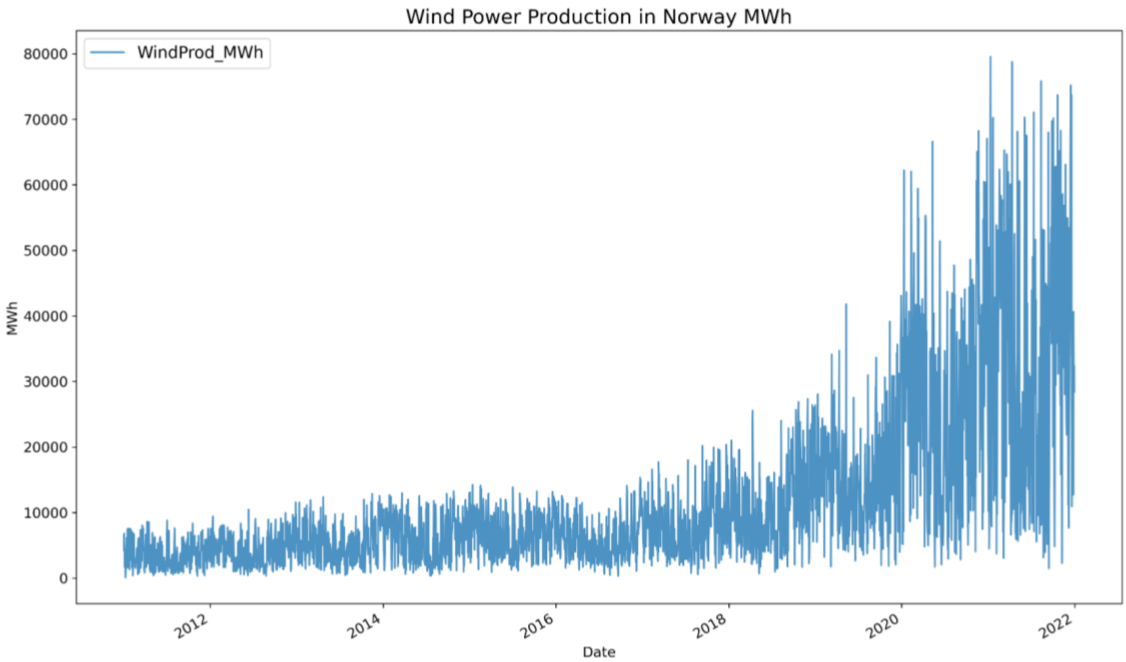


Figure 11: Wind power production 2011-2022 plotted using our dataset.

EU ETS CO2 allowances

The EU Emissions Trading System (EU ETS) is a cap-and-trade system established by the European Union to achieve its greenhouse gas reduction targets. The EU ETS can be seen as a green initiative as it aims to drive down emissions in a cost-effective manner and promote the transition to a low-carbon economy.

The system sets a cap on the total amount of carbon dioxide (CO2) that can be emitted by certain industries and allocates CO2 allowances to companies. Companies that emit more CO2 than their allocated allowances must purchase additional allowances, while companies that emit less CO2 can sell their surplus allowances to others. This creates a market for CO2 allowances and creates an economic incentive for companies to reduce their emissions. The

EU ETS prices represent the cost of emitting one ton of CO2. We have daily data from 2011-2022 shown in figure 12, the data is retrieved from Energi og Klima. (Energi og Klima, 2023).

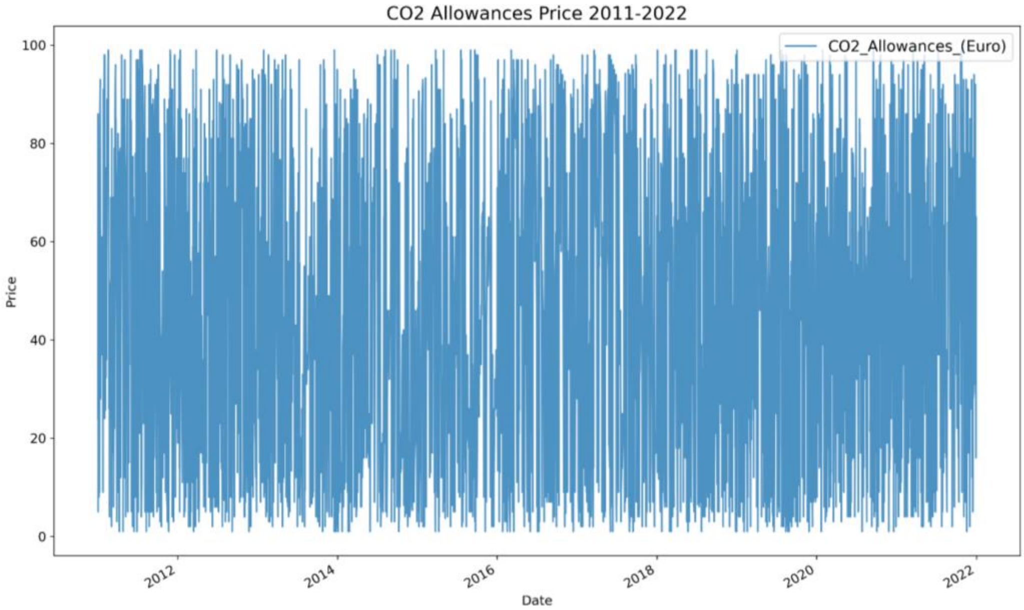


Figure 12: Price of CO2 Allowances 2011-2022 plotted using our dataset.

Electrification of the Norwegian continental shelf

Furthermore, as one of our independent variables of choice, we have elected to examine the electrification of the Norwegian continental shelf, specifically the transfer of power from land to the continental shelf in terawatts. The Norwegian Water Resources and Energy Directorate (NVE) has predicted that, in the long term, the average electricity price in Norway will experience an increase of approximately 7 to 10 Norwegian øre per kWh because of electrification measures (NVE, 2020, p. 38). One limitation of the electrification of the continental shelf data, is that it is only available on a yearly basis. To mitigate this constraint, we had to interpolate the data daily. This allows us to analyze trends over time, but also results in the loss of daily fluctuations this is clearly seen in the figure 13.

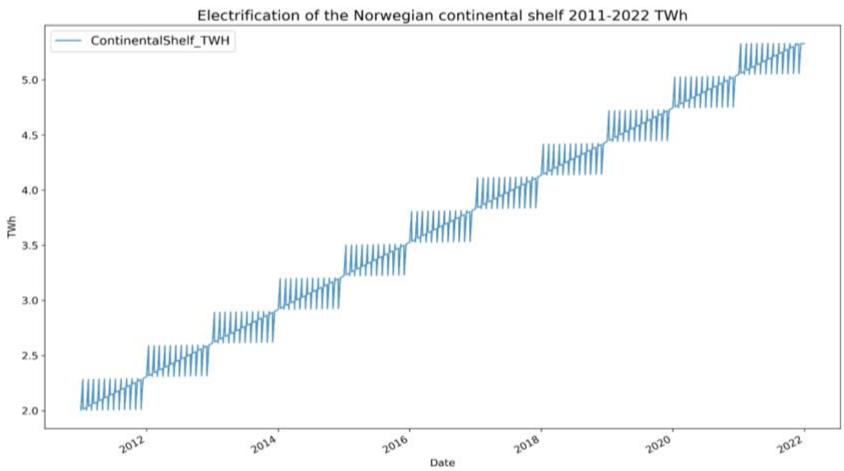


Figure 13: Electrification of Norwegian continental shelf 2011-2022 from dataset.

Electrification of the Norwegian Car Fleet

The electrification of the Norwegian car fleet is a trend that has gained significant momentum in recent years. We sent an email to "Opplysningsrådet For Veitrafikken" (OFV) and got data on the monthly number of newly registered electric cars in Norway from 2011-2021. The number of vehicles has been steadily increasing, with a significant spike in recent years seen in figure 14. This green initiative has the potential to significantly impact the electricity price in the country.

As more and more electric cars are put on the road, the demand for electricity for charging these vehicles will also increase. This increased demand for electricity, coupled with a limited supply, may lead to an increase in electricity prices. Furthermore, the charging of electric cars is expected to take place primarily during off-peak hours when electricity prices are lower, which may further strain the electricity grid and potentially increase prices. In conclusion, the electrification of the Norwegian car fleet is a critical aspect that must be carefully monitored to ensure that it does not lead to an unintended increase in electricity prices.

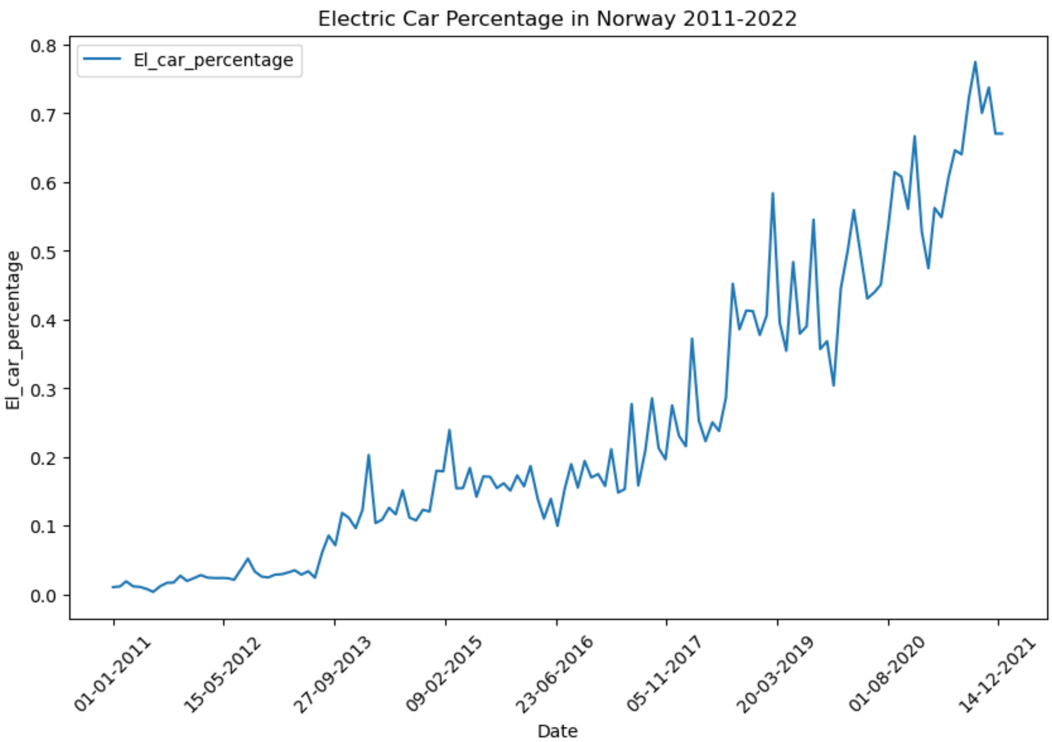


Figure 14: Percentage of electric cars in Norway 2011-2022 plotted from dataset.

5. Analysis

We want to investigate whether the inclusion of green initiative variables can help us create a better OLS model with both better explanatory and predictive capabilities. Our analysis is divided into three parts, starting with a correlation analysis to identify any significant relationships between the variables. We will then perform multiple linear regression to model the relationship between the electricity price and the green initiative variables. Finally, we will evaluate our model's performance and compare using prediction, Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

Correlation analysis

Heatmap

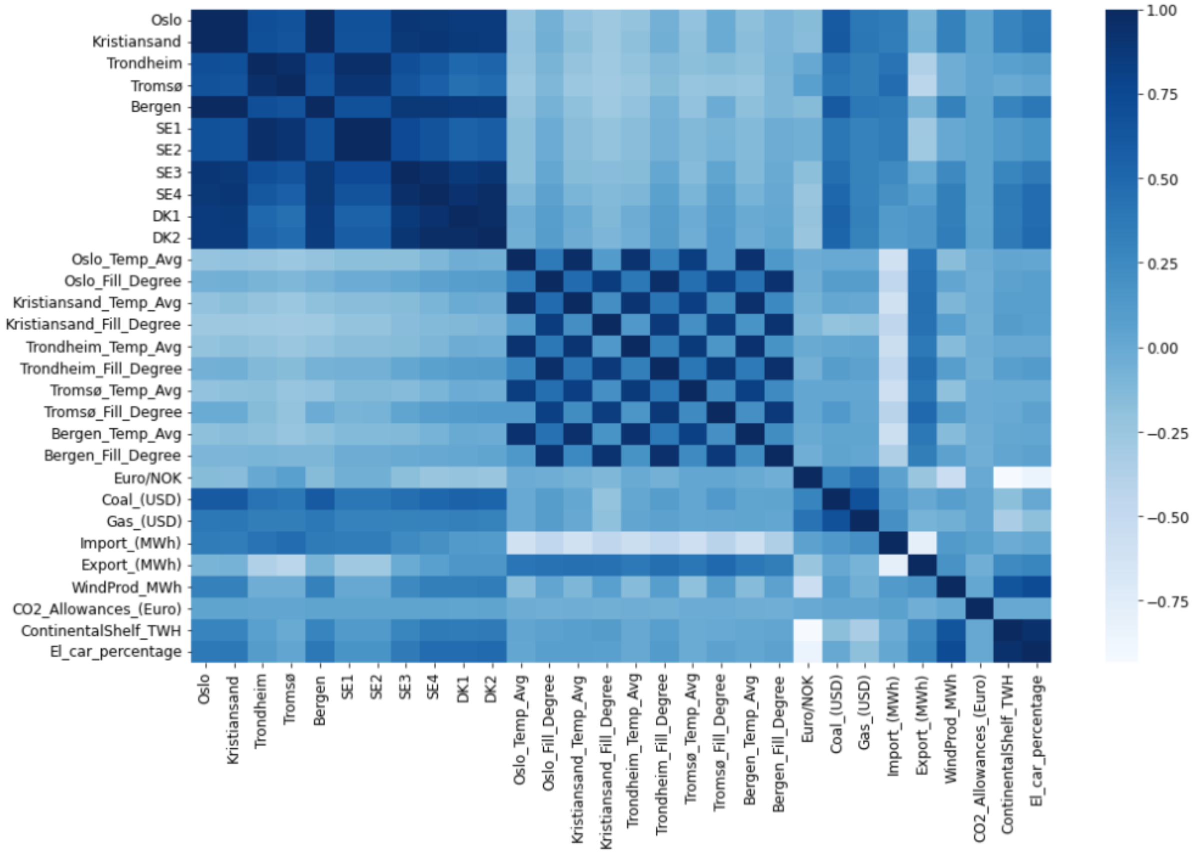


Figure 15: Heat Map generated using our dataset and the Seaborn library in Python.

The correlation matrix heatmap shown in figure 15 gives us a lot of information which can be overwhelming. However, it offers an overview of what kinds of variables are most correlated with the electricity price in Oslo (NO1). Figure 4 below shows a list of the different correlations starting from the most highly correlated. To sum up some of the findings:

Significant positive correlations

Other power zones (Bergen, Kristiansand SE/DK etc)

This makes sense as the different power zones are highly interconnected, however zones like Trondheim and Tromsø are much less correlated than zones like Bergen and Kristiansand due to being further away from Oslo.

Coal and Gas

We observed a high correlation between coal and the electricity price in Oslo with a coefficient of 0.60, as well as gas at 0.39 This makes sense if the electricity price is high (for instance during winter) the need for alternative energy sources like coal and gas would also be high.

Electric car percentage (El_car_percentage)

This is a highly interesting find, but we should be cautious to mix correlation with causality. Meaning that just because we have a significant positive correlation does not mean that a rise in the percentage of electric cars on the road is the cause of higher electricity prices. Perhaps it is just a coincidence? This is a find that needs further analysis before any conclusions can be made.

Variables	Correlation
Oslo	1.000000
Bergen	0.996965
Kristiansand	0.996170
SE3	0.891307
SE4	0.885585
DK1	0.858582
DK2	0.856878
Trondheim	0.696950
SE1	0.682073
SE2	0.681872
Tromsø	0.668294
Coal_(USD)	0.603618
Gas_(USD)	0.391858
El_car_percentage	0.384419
Import_(MWh)	0.352840
WindProd_MWh	0.314733
ContinantalShelf_TWH	0.290020
CO2_Allowances_(Euro)	0.047927
Kristiansand_Fill_Degree	-0.266129
Oslo_Temp_Avg	-0.217484
Trondheim_Temp_Avg	-0.204058
Tromsø_Temp_Avg	-0.198885
Kristiansand_Temp_Avg	-0.197804
Bergen_Temp_Avg	-0.184450
Euro/NOK	-0.153010
Bergen_Fill_Degree	-0.097744
Export_(MWh)	-0.083776
Oslo_Fill_Degree	-0.062766
Trondheim_Fill_Degree	-0.060678
Tromsø_Fill_Degree	-0.015097

Figure 16: Correlation with Oslo.

Import

We found a positive correlation of 0.35, which makes sense as when the demand for electricity in Oslo is high, the electricity price will likely also increase, leading to importing electricity becoming more desirable.

Wind Power Production (WindProd_MWh)

A positive correlation of 0.31 here is another example of a situation where you should be careful to confuse correlation with causality, as it goes against logic that higher production of electricity will lead to a higher price, that being said high electricity prices might incentivize the need to build more wind power plants, further increasing the production capability.

Continental Shelf (ContinentalShelf_TWh)

There is a positive correlation of 0.29 between the Oslo electricity price and the power consumption of the Continental Shelf. A moderate correlation that might be due to the high consumption increase as the Norwegian government wants more of the oil production to be powered by electricity. This increase likely increases the demand leading to increasing electricity prices.

Significant negative correlations

Kristiansand fill degree

With a coefficient of -0.266 it is the most significant negative correlation with the Oslo electricity prices (NO1). This came as a bit of a surprise, as you would think the Oslo fill degree would have a more significant correlation than the fill degree of Kristiansand. This might be a coincidence or perhaps this is a result of the connected nature of the southern power zones in Norway, meaning that the fill degree of the different zones in the south are highly correlated.

Oslo temperature average

The Oslo temperature average shows a significant negative correlation with the Oslo electricity price with a coefficient of -0,217. This is not very surprising as it is a known fact that weather and electricity prices have a close relationship. In Norway the climate is rather cold, in the winter months lower temperatures lead to higher demand for heating which again leads to higher electricity prices. In summer the opposite happens, higher temperatures lead to lower need for electricity for heating which again leads to lower electricity prices. This explains why the correlation is negative and not positive.

OLS Multiple Linear Regression

The analysis has led us to the correlation of the different variables and how they are correlating upon each other. In this section we are using them in the explanatory OLS multiple linear regression model to find a relationship between all the variables and try to predict the price based on it. The base model is without the green initiatives as variables and the second model includes the green initiatives. We are using R-squared, AIC and BIC to measure the performance and to compare the models to each other. Furthermore, we will be looking at the p-values of the different parameters of the models to see if they are statistically significant.

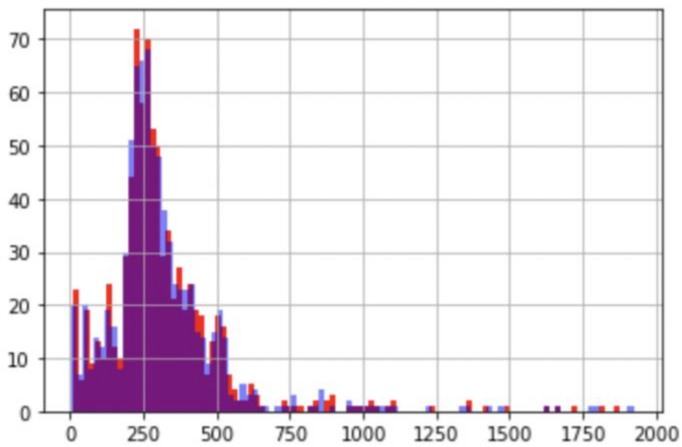
Base model

Variables	Parametres
Kristiansand	0.463596
Trondheim	0.017377
Tromsø	0.038766
Bergen	0.504569
SE1	0.026966
SE2	-0.060965
SE3	0.044989
SE4	-0.026589
DK1	-0.057646
DK2	0.065575
Oslo_Temp_Avg	0.195530
Oslo_Fill_Degree	6.190459
Kristiansand_Temp_Avg	-0.842968
Kristiansand_Fill_Degree	-11.224522
Trondheim_Temp_Avg	-0.430511
Trondheim_Fill_Degree	-17.688397
Tromsø_Temp_Avg	0.530512
Tromsø_Fill_Degree	23.964586
Bergen_Temp_Avg	0.054470
Bergen_Fill_Degree	2.698950
Euro/NOK	-118.010876
Coal_(USD)	0.049778
Gas_(USD)	-0.259805
Import_(MWh)	-0.000008
Export_(MWh)	-0.000003

Intercept	20.937508

R^2	0.995642
AIC	26629.639198
BIC	26787.596259

Test data prediction



Predicted data vs. Test data	
R^2	0.994101
MSE	278.804701
RMSE	16.697445
MAE	6.754880

Figure 17: OLS-model trained with base-model data (80/20 training/test set).

Our intercept indicates that given all the other variables are 0, the daily average electricity price in Oslo would be 20.94 NOK - which does not make any sense given none of these variables will ever be 0 at the same time, or 0 at all. We will therefore look away from the intercept. Looking at our coefficients, we can spot that the Euro/NOK cash balance has a substantial negative effect on the Oslo price - also the filling degrees of the water reservoirs seem to have a negative effect. Simplified, this means that a one unit change in EUR/NOK balance will change the Oslo price by -188.01.

It is important to note however that while looking at all the variables, the size of the coefficients may be affected by the different measurement units and does not indicate the overall effect - looking at our correlation analysis, we can see that the Coal price has a high correlation with the Oslo spot price, but a low coefficient in the OLS-model.

It is also important to keep in mind that we cannot establish a causal effect, and that these variables most likely are affected by each other. For example, the price in Trondheim may be affected by the Oslo price. Gas price might also affect the EUR/NOK relationship considering the Norwegian economy is highly affected by the export of fossil fuels like oil and gas.

P-Values

In order to see if the parameters are statistically significant, we can look at the p-value. A p-value below 0,05 is generally seen as significant. In figure 18 we see the p-values extracted from the base model OLS model. The significant variables are marked in green. For the base model the number of significant variables is 13, with a percentage of significant variables of 52%. Comparing this with the percentage of significant variables in the green model can be good metric to compare the explanatory power of the two models.

Variables	P-Values
Kristiansand	0,000
Trondheim	0,050
Tromsø	0,000
Bergen	0,000
SE1	0,468
SE2	0,249
SE3	0,000
SE4	0,000
DK1	0,000
DK2	0,000
Oslo_Temp_Avg	0,918
Oslo_Fill_Degree	0,714
Kristiansand_Temp_Avg	0,011
Kristiansand_Fill_Degree	0,572
Trondheim_Temp_Avg	0,000
Trondheim_Fill_Degree	0,011
Tromsø_Temp_Avg	0,000
Tromsø_Fill_Degree	0,000
Bergen_Temp_Avg	0,551
Bergen_Fill_Degree	0,517
Euro/NOK	0,450
Coal_(USD)	0,189
Gas_(USD)	0,808
Import_(MWh)	0,000
Export_(MWh)	0,833

Figure 18: Table with P-values from the base model

Performance

Even though our goal is to make an explanatory-focused model, testing the model's predictive capability will give us an indication on how well the model catches the underlying relationships between our dependent variable and independent variables.

The data was split into 80% training data and 20% test data, to provide the model enough data while keeping a reasonable chunk for testing. When predicting using the test data, our model shows a R-squared score of 0.994101 - which indicates the variability of the model explained by the data. In other words, this is the explanatory power of our model. This is a substantially high number, which tells us our model has a good fit.

Looking at the bar-plot, our data distribution looks quite similar between the predicted and the real testing data. The test data (red) has a mean value of 315.9112, while the predicted data (blue) has a mean value of 315.2665 - which tells us that the model does a good job of capturing the distribution of the Oslo spot price given the independent input variables.

The RMSE (Root mean squared error) explains how well the model's predictions match with the actual values, where a lower score indicates a better model. We received a score of 16.697445. MAE (Mean absolute error) provides us information about the differences between predicted and real values in the form of absolute values. We were given a score of 6.74880. These values tell us very little without a point of comparison, which is why we will discuss these later in comparison with our green initiatives model.

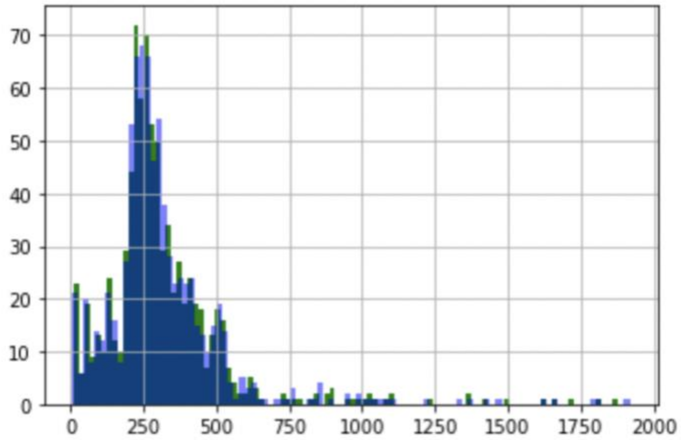
Green-initiatives model

Variables	Parametres
Kristiansand	0.461466
Trondheim	0.015641
Tromsø	0.039657
Bergen	0.504596
SE1	0.021860
SE2	-0.054872
SE3	0.044279
SE4	-0.025287
DK1	-0.057126
DK2	0.065277
Oslo_Temp_Avg	0.187224
Oslo_Fill_Degree	5.906788
Kristiansand_Temp_Avg	-0.872192
Kristiansand_Fill_Degree	-19.053920
Trondheim_Temp_Avg	-0.412279
Trondheim_Fill_Degree	-15.089045
Tromsø_Temp_Avg	0.505705
Tromsø_Fill_Degree	24.237129
Bergen_Temp_Avg	0.064237
Bergen_Fill_Degree	5.880568
WindProd_MWh	0.000010
CO2_Allowances_(Euro)	0.011189
Euro/NOK	-32.137737
Coal_(USD)	0.049882
Gas_(USD)	-0.296532
ContinentalShelf_TWh	3.386481
Import_(MWh)	-0.000008
Export_(MWh)	-0.000002
El_Car_Percentage	-11.510317

Intercept	1.955939

R^2	0.995652
AIC	26630.058317
BIC	26812.316464

Test data prediction



Predicted data vs. Test data	
R^2	0.994212
MSE	278.8047010
RMSE	16.697445
MAE	6.754880

Figure 19: OLS-model trained with the green-model data (80/20 training/test set).

The aim of the green initiatives model is to take our green initiatives variables into account for a potentially improved model. In this case, we control for:

- El_Car_Percentage: ratio of electric vehicles amongst the Norwegian car fleet
- ContinentalShelf_TWh: export of electricity from the main to the Norwegian continental shelf to the oil drilling rigs.
- CO2_Allowances_(Euro): The price of CO2-quotas in the EU CO2 allowance system
- WindProd_MWh: production of renewable energy by wind powered turbines.

From the model's coefficients, ContinentalShelf_TWh seems to change the electricity price in Oslo by 3.3848 per unit TWh. We should however be careful to draw conclusions considering the danger of mediating variables, especially considering the electricity market is highly complicated. El_Car_Percentage seems to have a negative effect with a coefficient of -11.5103. CO2_Allowances_(Euro) is surprising considering we were expecting a more drastic effect on the spot price, with a low coefficient of 0.0112 - this could be due to a weak relationship with Oslo or the variable being highly correlated with another variable like Coal price or spot price in one of the surrounding zones. The same goes for WindProd_MWh, which has a coefficient of 0, which might be due to another variable picking up the effect.

P-Values

In figure 20 we see the p-values extracted from the green model OLS model. Again, we see the significant variables marked in green. For the base model the number of significant variables is 16, with a percentage of significant variables of 55,17%. This is higher than the percentage of significant variables in the base model of 52%, indicating that the model including the green initiative has a better explanatory power.

Variabels	P-Values
Kristiansand	0,000
Trondheim	0,219
Tromsø	0,000
Bergen	0,000
SE1	0,681
SE2	0,398
SE3	0,000
SE4	0,000
DK1	0,000
DK2	0,000
Oslo_Temp_Avg	0,985
Oslo_Fill_Degree	0,065
Kristiansand_Temp_Avg	0,000
Kristiansand_Fill_Degree	0,000
Trondheim_Temp_Avg	0,000
Trondheim_Fill_Degree	0,011
Tromsø_Temp_Avg	0,000
Tromsø_Fill_Degree	0,000
Bergen_Temp_Avg	0,454
Bergen_Fill_Degree	0,120
WindProd_MWh	0,531
CO2_Allowances_(Euro)	0,751
Euro/NOK	0,491
Coal_(USD)	0,217
Gas_(USD)	0,923
ContinentalShelf_TWH	0,000
Import_(MWh)	0,000
Export_(MWh)	0,133
El_car_percentage	0,000

Figure 19: Table with P-values of new model

Performance

The model shows a R-squared score of 0.9942 when predicting on the test data, which is slightly better than our base-model. Furthermore, we get a RMSE of 16.6974 and a MAE of 6.7549. Looking at our distribution, the predicted Oslo spot price seems to be distributed quite similar to the test data, which indicates that also our green model performs well.

Model comparison

Looking at the base model versus the green model, we can conclude that the base model scores lower on AIC and BIC, which indicates that the model has a better fit when taking the complexity into account. Therefore, it seems like the base model would be the better choice in explaining the NO1 spot price.

Number of significant variables	
Base-Model	13
Green-Model	16
Percentage of significant variables	
Base-Model	52 %
Green-Model	55,17 %
Difference	**3,17 %**

	Base-model	Green-model	difference
AIC	26629,6392	26630,05832	0,419119
BIC	26787,59626	26812,31646	24,720205

Figure 20: Significant p-values of variables and model AIC, BIC comparison.

Further, the reason for lower AIC and BIC suggests that the trade-off between the model complexity and goodness of fit is better for the base model. This might suggest that the green initiatives do not in fact help explain the NO1 spot price, or at least improve the OLS model. Also, looking at the p-values; CO2_Allowances_(Euro) and WindProd_MWh have high p-values which indicate that the observed coefficient is not statistically significant. This means that the observed coefficient might be due to chance and may prove to not have any explanatory power in our dependent variable Oslo. However, we see that the overall percentage of statistically significant variables increase with the introduction of the green initiatives slightly with a difference of 3,17%. This suggests a small increase of the explanatory power of the model, nevertheless this difference is small and might not be practically significant. As we mentioned earlier, because of missing data, we had to interpolate some of the variables, which might explain the high p-values. This might be due to the “averaging” of the data through interpolation, removing the underlying patterns.

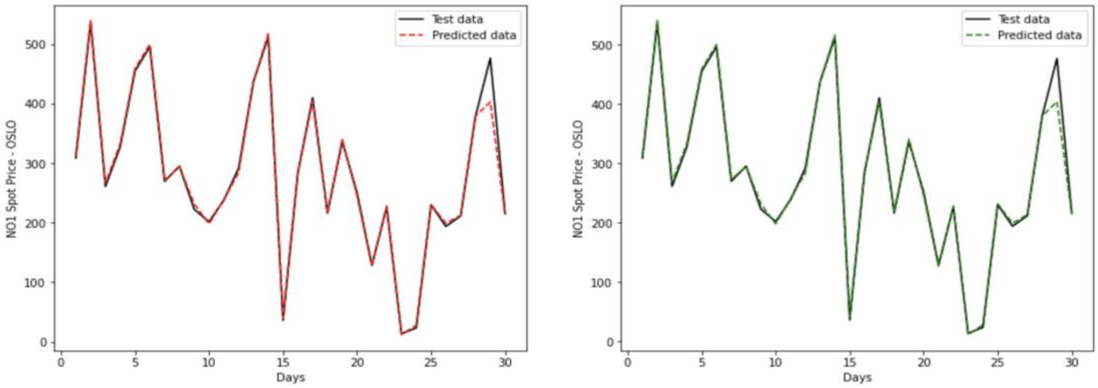


Figure 21: Base-model and green-model in prediction of NO1 Spot price (last 30 days, test data).

Finally, in examining if our OLS-models have good explanatory power, we might also examine their predictive capabilities. In figure 22 above, we have plotted the actual test data (solid line), against the predicted data (dotted line), for the last 30 days in the test data. Looking at the plots, the predictions look surprisingly similar between both models suggesting the green independent variables did not play a significant role in improving the model. This is confirmed through the RMSE, MSE and MAE, where both models provide the same scores on the test set. The models seem to predict surprisingly well in both versions. A potential reason for this might be overfitting, even though we did test the models through splitting the data into training and test sets. Overfitting might still occur due to the test set being substantially like the training set, which might be our case. This might be due to our models picking up on some noise or random fluctuations in our training data, which might not always be the case in new data. Further on all the time-series data that are used is not stationary data. A problem that can occur when this is the case is spurious regression. An example is for the green initiative's variable "El_car_percentage", "ContinentalShelf_TWh" and "WindProd_MWh". None of these variables are stationary potentially leading to a misleading statistical result because of the possibility that two or more of the time series have similar trends. This can lead to high correlations even if there is no real causal relationship between any of them. (Phillips P.C.B, 1986) Based on some of the arguments we should therefore be careful in drawing any conclusions regarding the models predictive and explanatory capabilities.

6. Conclusion

To conclude this thesis, we will start by concluding both our work so far, findings, implications and potential further research. By reviewing relevant literature, we found necessary and highly relevant variables for explaining and predicting the Norwegian electricity price. By doing so, we managed to establish a base model based on the OLS approach. To further try and improve this model, we tried to implement additional variables measuring relevant and highly discussed green initiatives. These include electrification of the continental shelf, national car fleet, EU CO2 quota prices and production of renewable energy through wind turbines.

By doing a correlation analysis, we found that the nearby power-grid zones had the highest correlation with the NO1 spot price (Oslo). Furthermore, Coal_(USD) and Gas_(USD) seemed to also have significant correlations. El_car_percentage did also seem to have a correlation, although not especially high. Having this in the back of our minds, we chose to split the data into 80/20 training/test sets to be able to evaluate the model with “unused” data. The models were trained with all the variables without removing any of the lower correlating variables. The models were then tested and evaluated, which brings us back to our thesis problem:

Can the inclusion of green initiatives variables help us explain the electricity price more accurately?

Our findings can be concluded as doubtful. We did not see any improvements by controlling for the additional variables in the OLS model, which can be reflected through both a higher AIC and BIC score for the adjusted green initiatives model. The p-values for some of green initiative variables were also considered high, suggesting the coefficients have low credibility. We discussed that this might be due to the interpolating of the missing data. Therefore, we suggest discarding the green model, considering the base model performed better. Looking at their predictive capabilities, both models were able to predict the last 30 days of the test set exceptionally. This should however be a reason for being critical, considering the danger of over-fitting. Even though we did split both models into training and test sets, our data as whole might have underlying patterns and similarities which would not be present in newer data.

Sources of error and further work

Like mentioned, the lower correlating variables were not removed which might also increase our risk of overfitting. This can be reflected through the lower AIC and BIC score when comparing the base model to the model with additional green-initiative variables. The model should therefore be "trimmed" through forward selection by removing low correlating variables until a better R-squared is achieved. Also, we have concerns regarding the models being overfitted, this is reflected through the surprisingly accurate predictions. As we discussed, this might be due to similarities and underlying patterns in the data which was later split into the training and test set. To test for overfitting, the models should be further evaluated through new data. A issue with not using statistical tests that could accurately check for stationarity in the dataset, we also miss the possibility to check for spurious regressions. This can affect the R-squared based on underlaying trends. A plausible approach for this problem is can be to the Augmented Dickey-Fuller (ADF) test on the datasets. The results from this test can further be used as an indicator to which of the dataset we should make more stationary before the analysis. By conducting the ADF test, we can prevent a misrepresentation of R-squared in a more efficient way.

Lastly, due to lack of available data, some choices had to be made to complete the dataset. Both the data on the continental shelf electricity export and CO2_allowances had to be interpolated to fit into the timeframe of days. This has caused the data to be "averaged" and flattened, removing fluctuations and potential patterns. This might have caused the data to be sub-optimal for training the model and has weakened the model's explanatory- and predictive capabilities. To address this in the future, there should be more precise data. Also, there are other green initiatives which were left out, like electrification of the land-based industry. We were not able to obtain any relevant data on this, which is why it was left out. Further work should therefore include researching other potentially relevant variables, which might have a bigger correlation with the spot price.

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